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Optimization of supply air flow and temperature for VAV terminal unit by artificial neural network

Hyo-Jun Kim [a], Young-Hum Cho [b,*]

[a] Institute of Industrial Technology, Yeungnam University, South Korea
[b] School of Architecture, Yeungnam University, South Korea

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ABSTRACT

The purpose of this paper is to optimize the supply air flow rate and temperature of the variable air volume (VAV) terminal unit by artificial neural network (ANN). In general, the setpoint of the VAV terminal unit are supply air flow rate and supply air temperature. These setpoints are determined by the design value, and are calculated by the maximum indoor heating/cooling load and the ventilation requirements. The setpoints calculated based on the design value does not cause any problems in maintaining the indoor environment. However, energy consumption cannot be optimized because it is based on the maximum design value. In order to improve the existing control method, it is important to apply the setpoints according to the real time indoor conditions. The real time indoor condition can be utilized for control through prediction model. In this study, the indoor load, indoor air quality and energy consumption were predicted and used for VAV system control. In addition, the predictive model was developed with the ANN algorithm, and the process of selecting input data and optimizing the predictive model was performed. The performance of the ANN based optimal control algorithm (suggested CASE) for the VAV terminal unit in the target building was compared with those of the dual maximum control algorithm (existing CASE), one of the VAV terminal unit control algorithms. The comparison of heating season showed that the ANN based control algorithm of VAV terminal unit reduced 16.7% of supply fan energy consumption and 19.5% of reheat coil energy consumption compared to the existing CASE using the fixed setpoint.

1. Introduction

Variable air volume (VAV) systems became widespread in the mid-1970s as a result of the global energy crisis [1]. In the 1980s, the development of measurement technology and sensors accelerated, and pressure-independent control became possible [2]. In the 1990s, with the advent of programmable Direct Digital Controls (DDCs), the scope of control implementation expanded [3]. The control performance of the VAV terminal unit affects the comfort of the occupants and the energy consumption of the building. Therefore, indoor discomfort to the occupants and energy waste problems may occur depending on the set point in the VAV terminal unit. In general, the ASHRAE Fundamental [4] suggests fixed, supply airflow rate and temperature setpoints in the VAV terminal unit of occupied space. Stein [5] presented the maximum cooling and heating airflow rates to be set in the VAV terminal unit in a building. In particular, the maximum airflow rate during heating was calculated based on the indoor heating load. The minimum air flow rate must satisfy the ventilation requirement and the indoor load. Also, it must set to 20% or less of the maximum air flow rate. However,

* Corresponding author.
E-mail address: yhcho@ynu.ac.kr (Y.-H. Cho).

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due to the fixed, set supply airflow rate and temperature values of the study, it was impossible to reflect the dynamic indoor condition of the building, and heating energy might be wasted if the heating load was large. One way to solve this energy waste is to predict the actual indoor condition of the building in real-time and set the supply airflow rate and temperature accordingly. This prediction derives the relationship between the actual indoor condition and the setpoint of the corresponding VAV terminal unit as a mathematical model based on theoretical knowledge. The prediction also presents the setpoints in real-time accordingly, which requires a lot of experience and related knowledge.

Cho and Liu [6] suggested a method to reset the minimum air flow rate. The suggested method derives the minimum air flow rate that satisfies the indoor air quality (CO_2 concentration) and indoor heating load. And the supply air temperature was reset according to the indoor heating load. The suggested method was applied and verified through theoretical analysis, simulation and field experiments. Kang et al. [7] proposed an algorithm to reset setpoints of supply air temperature and minimum air flow rate. The reset setpoints consider the floor height, CO_2 concentration and indoor heating load. The control performance of the algorithm was evaluated for room temperature, air quality and stratification through TRNSYS simulation. Kim et al. [8] proposed control algorithm without stratification of VAV terminal unit. The air flow rate and supply air temperature were presented that do not occurring temperature stratification according to the indoor sensible load. And the performance of proposed control algorithm was evaluated through TRNSYS simulation. Liu [9] proposed a method of controlling the demand ventilation of a building by using the occupancy sensor instead of a carbon dioxide (CO_2) concentration sensor used in the existing demand controlled ventilation (DCV) of the VAV terminal unit. Kim et al. [10] proposed control algorithm of VAV system that satisfies the ventilation requirements in multi-zone building. A supply air flow rate control method linking air flow rate of VAV terminal unit, AHU and outside air flow ratio was developed and verified through TRNSYS simulation. Zhu [11] proposed a method to optimize the installation location and number of indoor temperature monitoring sensors. The VAV terminal control method according to the optimal indoor temperature sensor was evaluated using computational fluid dynamics (CFD) simulation. The proposed control method improved indoor thermal comfort performance and air diffusion performance index (ADPI). However, the control method based on a mathematical model suggested in these existing studies requires a lot of expert knowledge, information, and additional physical sensors.

The existing control of heating, ventilation and air conditioning (HVAC) system was limited due to indoor environmental and system operation monitoring and control of setpoints by the manager [12]. In recent research [13], existing HVAC control methods are improved through the development of optimal control and operation of building systems using data-driven models. The data-driven model, also called the black box model, divides the data collected from the building into input and output data and predicts it through probability and statistical methods [14]. Data-driven models can create predictive models with low expertise compared to existing white box models. This can be used with high utility in building automation system (BAS) where a lot of data is collected [15].

The machine learning method, one of the data-driven models, can predict the linear and nonlinear relationship between the input and output data, so it is suitable for predicting the nonlinear relationship of the building system, and many studies are being conducted. Li et al. [16] developed a support vector machine-based cooling load prediction model through five inputs (solar radiation, etc.). Simon [17] developed cooling load prediction model using the neural network model through four inputs (weather data, etc.) in Hong Kong. Sholahudin and Han [18] developed artificial neural network (ANN) based heating and cooling load model using weather data (wind speed, etc.). Pedro et al. [19] developed ANN based short-term building load prediction model through temperature, hour and day as input data.

Edwards et al. [20] predicted the monthly electrical consumption through 150 input data using seven different machine learning algorithms (support vector machine, etc.). Sala-Cardoso et al. [21] suggested recurrent neural networks based power consumption model using usage pattern of the buildings for advanced strategies of resource management. Ahmad et al. [22] developed an energy prediction model and compared performance that using feed-forward back-propagation ANN and random forest. Garnier et al. [23] proposed ANN based energy prediction model through indoor environmental value such as indoor temperature, radiant temperature, etc. The proposed prediction model was used for model predictive control (MPC) for energy consumption minimization of HVAC system. Platon et al. [24] developed prediction model of hourly electricity consumption using ANN and case-based reasoning (CBR), and compared prediction performance.

The control method of the existing VAV terminal unit uses fixed setpoints (maximum air flow rate, minimum air flow rate, supply air temperature). In order to improve existing control method, a control method was proposed by resetting the setpoint using a mathematical model. The mathematical model used in the study of the VAV terminal unit control method has a limitation in collecting input information for developing the expert knowledge and model, so data-based prediction model development is required. Most of the existing study of ANN-based prediction model use weather data, indoor environmental data and design information as input data. However, it is necessary to improve the prediction model by using the indoor operating data of the VAV system (supply fan speed, damper opening ratio, etc.). In addition, it is necessary to predict the indoor load and indoor CO_2 concentration, which are important factors in deriving the air flow rate and supply air temperature setpoints of the VAV terminal unit. Energy consumption is required to select a setpoint by predicting the minimum energy consumption according to variable setpoints. Therefore, this study develop ANN based indoor load, CO2 concentration and energy consumption prediction model. And optimization of control method develop that can reset the setpoint (supply air flow rate and temperature) in real time using prediction models.

2. Methodology

2.1. Dual maximum control logic of VAV terminal unit

In general, the recommended control sequence for VAV terminal unit is dual maximum control logic [4,25]. Fig. 1-(a) shows schematic diagram of VAV terminal unit and Fig. 1-(b) shows dual maximum control sequence. The dual maximum control logic sets the minimum air flow rate, the maximum cooling and heating air flow rate and maximum supply air temperature. The supply air flow rate is adjusted according to the air flow setpoint for indoor temperature sensor. In addition, when the heating load increases in the heating mode, the supply temperature and the supply air flow rate increase. The supply temperature and air flow rate are related to the indoor load. Equations (1) and (2) can be used to calculate the supply temperature and air flow rate for the indoor load. In addition, the supply air flow rate that satisfies the indoor air quality can be expressed as Equation (3) according to the CO_2 concentration. As such, the indoor load and CO_2 concentration are very important factors for controlling the supply air flow rate and temperature of the VAV terminal unit.

$$\dot{m}_{load} = \frac{q_r}{C_p(T_s - T_r)} \tag{1}$$

$$T_{s,load} = \frac{q_r}{\dot{m}C_p} + T_r \tag{2}$$

$$\dot{m}_{IAQ} = \frac{G(1 - e^{-I})}{C_{in} - C_o - (C(0) - C_o)e^{-I}} \tag{3}$$

where

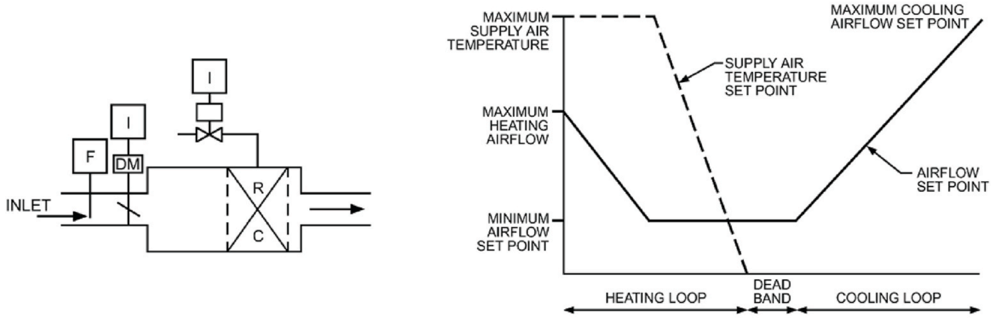
$\dot{m}_{load}$Supply air flow rate according to indoor load, kg/s
$\dot{m}_{IAQ}$Supply air flow rate according to indoor air quality, kg/s
$T_{s,load}$Supply air temperature according to indoor load, K
q_rIndoor load, W
$C_p$specific heat capacity of the fluid, J/(kgK)
T_sSupply air temperature, K
T_rIndoor temperature, K
Gindoor CO_2 generation rate of the building, ppm
Iindoor ventilation rate of the building
C_{in}indoor CO_2 concentration of the buildin, ppm
$C_o$supply CO_2 concentration, ppm
$C(0)$initial indoor CO_2 concentration, ppm

2.2. ANN based prediction model

In general, the setpoint of the VAV terminal unit are based on the occupied space heating/cooling load and air quality. However, setpoint of supply airflow rate is calculated based on the design maximum load of the target zone. And the setpoint of supply airflow rate considering ventilation requirements is also selected based on the maximum occupants in target zone. Therefore, if the indoor load, air quality and energy consumption of the target zone are predicted, the setpoint of the VAV terminal unit system can be reset in real time.

ANN is a method that mimics the neurons of the human brain and is a representative algorithm of machine learning. ANN can predict nonlinear patterns with superior performance compared to other black-box models [26]. Based on these capabilities, ANN is being actively used in the building field [27–29]. By being able to model the non-linear pattern of building energy through previous studies, it has also been proven that it is more reliable in predicting the energy consumption of buildings than other existing statistical based methods [30,31].

The prediction performance of the ANN model is determined by the input data performance. Therefore, determining the input data is a very important factor [32]. The indoor load is related to the air conditioning load as shown in Equation (4), which can be calculated using the first law of thermodynamics [33]. The input data of indoor load model were selected by comparing operation data and



(a) VAV terminal unit (Throttling type) (b) Dual maximum control logic

Fig. 1. Schematic diagram and control sequence of VAV terminal unit by ASHRAE Handbook [4].

theoretical models (Equation (4)) of VAV terminal unit. The input data of indoor load model were selected as supply fan speed, VAV damper opening ratio and outdoor air temperature.

$$q = \dot{m}C_p(T_{out} - T_{in}) = \dot{m}(h_{out} - h_{in}) \tag{4}$$

where

q heat transfer rate in the control volume, kJ/hr
$\dot{m}$ mass flow rate of the fluid, kg/s
T_{in} temperature of the fluid entering the control volume, K
T_{out} temperature of the fluid leaving the control volume, K
h_{in} enthalpy of the fluid entering the control volume, J/kg
h_{out} enthalpy of the fluid leaving the control volume, J/kg

Equation (5) is a mathematical model for indoor CO_2 concentration of target zone [34]. In this equation, the indoor CO_2 concentration is calculated using the volume of the target zone, the indoor CO_2 generation rate of the building, the initial indoor CO_2 concentration, and the supply CO_2 concentration and airflow rate of the VAV terminal unit in the target zone, as variables. Input data of indoor CO_2 prediction model were selected by comparing operation data and theoretical models (Equation (5)). Input data of indoor CO_2 prediction model were selected as number of occupants, supply fan speed, outdoor damper and VAV damper opening ratio.

$$C(t) = C_o(t) + \frac{G(t)}{Q(t)} + \left(C(0) - C_o(t) - \frac{G(t)}{Q(t)}\right)e^{-It} \tag{5}$$

with

V volume of the target zone, m^3
$C(t)$ indoor CO_2 concentration of the building at the time 't', ppm
$Q(t)$ supply airflow rate at the time 't', m^3/h
$C_o(t)$ supply CO_2 concentration at the time 't', ppm
$G(t)$ indoor CO_2 generation rate of the building at the time 't', ppm
$C(0)$ initial indoor CO_2 concentration, ppm

Equation (6)~(8) is a mathematical model for energy consumption of VAV system [8]. The input data of the energy consumption model should be predicted by setpoint of the supply air temperature and air flow rate that satisfy the indoor air quality and indoor load. The input data of energy consumption model were selected for indoor load, CO_2 concentration, supply air temperature and air flowrate setpoints.

$$E_c = \dot{m}\left(h_{coil,out} - h_{coil,in}\right) \tag{6}$$

$$E_{rh} = \dot{m}C_p(T_{dis} - T_s) \tag{7}$$

$$E_{fan} = \dot{m}C_p\left(T_{fan,out} - T_{fan,in}\right) \tag{8}$$

where

E_c cooling coil energy consumption, J
E_{rh} reheating coil energy consumption, J
E_{fan} fan energy consumption, J
$\dot{m}$ air flow rate, kg/s
T_{dis} temperature of the discharged air, K
T_s temperature of the supply air, K
$h_{coil,out}$ enthalpy of the air leaving the cooling coil, J/kg
$h_{coil,in}$ enthalpy of the air entering the cooling coil, J/kg
$T_{fan,out}$ temperature of the air leaving the supply fan, K
$T_{fan,in}$ temperature of the fluid entering the supply fan, K

2.3. ANN based optimal control of VAV terminal unit

2.3.1. Approach

The ANN based VAV terminal unit optimal control is based on the prediction of the indoor environment and energy consumption. After predicting the indoor condition, the energy consumption is predicted by changing the supply air flow rate and supply temperature. The prediction model development by ANN method uses operational data of VAV terminal unit. For the CO_2 prediction model, the outdoor air damper opening ratio, the supply fan speed, the VAV damper position and the number of occupants were selected as input variable. For the load prediction model, supply fan speed, VAV damper position, outdoor temperature and number of occupants were selected as input variable. For the energy prediction model, the CO_2 predicted value, the load predicted value, the setpoints of supply air flow rate and the supply temperature were selected as input variable. Repeat prediction for air flow rate and supply temperature within the operating range of the terminal unit. And the supply air flow rate and the supply temperature of the minimum energy condition are derived, and the results are used as the control setpoint of the VAV terminal unit. Fig. 2 shows concept of ANN based optimal control of VAV terminal unit.

As there was a limit to the data collected from the target building of this study, iterative simulations of the building were performed using TRNSYS17, a dynamic simulation tool. In particular, these simulations were performed by changing the variables that can affect the indoor conditions and energy consumption. The simulated results were then used to form an energy consumption prediction model. In particular, they were used as learning data to develop the machine learning based optimal control of the VAV terminal unit. The learning data was collected at 1 h intervals and by changing the indoor heat conditions and the setpoints of the VAV terminal unit. Finally, iterative simulation cases for different combinations of the variables were built, and the corresponding simulations were performed.

2.3.2. *ANN based optimal control algorithm*

Fig. 3 shows the ANN based optimal control algorithm of the VAV terminal unit. In particular, this algorithm satisfies the indoor comfort of the occupants and minimizes the energy consumption of VAV terminal unit through an ANN prediction model. The following are the algorithmic steps.

Step 1 Prediction of the indoor load and CO_2 concentration on next timestep of the building based on current operational data (outside temperature, outdoor damper opening ratio, supply fan speed, VAV terminal unit damper opening ratio and the number of occupants) of the VAV terminal unit by ANN.
Step 2 Prediction of the energy consumption on next timestep based on the indoor load and CO_2 concentration prediction models and the control setpoints (supply air flow rate and temperature) of the VAV terminal unit.
Step 3 Repeat the above steps 120 times (number of applicable setpoint cases; in this study, derived the 120 times repeated simulation by multiplying 15 air flow rate setpoints and 8 temperature setpoints) by changing the control setpoint within their respective ranges according to the indoor condition.
Step 4 Derivation of the minimum supply air flow rate and temperature setpoint on next timestep of the VAV terminal unit under the minimum indoor energy consumption condition.
Step 5 Input the derived setpoint as the control setpoint of the VAV terminal unit indoor for the next iteration of the algorithm. The algorithm is executed again from Step 1, which uses the operational data of the VAV terminal unit obtained at the end of the previous Step 5.

3. Case study

3.1. *Target building*

The target building of a chosen building for the validation of the ANN based optimal control algorithm of the VAV terminal unit is a laboratory with an area of approximately 116.64 m^2 and equipped with a single duct VAV system and a VAV terminal unit with a reheat coil. The details of the VAV system in target building are given in Table 1. The air conditioning system installed in the laboratory is operated 24 h a day, and the operating conditions are set to maintain the set temperature of the room at 24 °C. The system of the target building consists of a VAV system (with supply and return fan), and an air-cooled heat pump system. The rated air flow rate of the terminal unit is 1360CMH, and rated capacity of reheating coil is 4000 kcal. The supply fan and return fan are frequency controlled

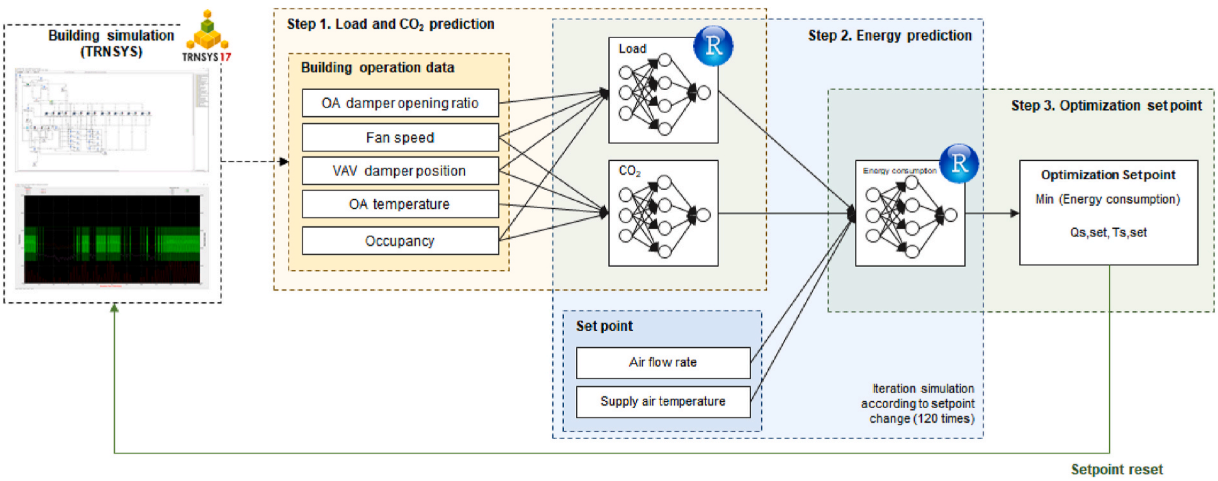


Fig. 2. Schematic diagram of ANN based optimal control of VAV terminal unit.

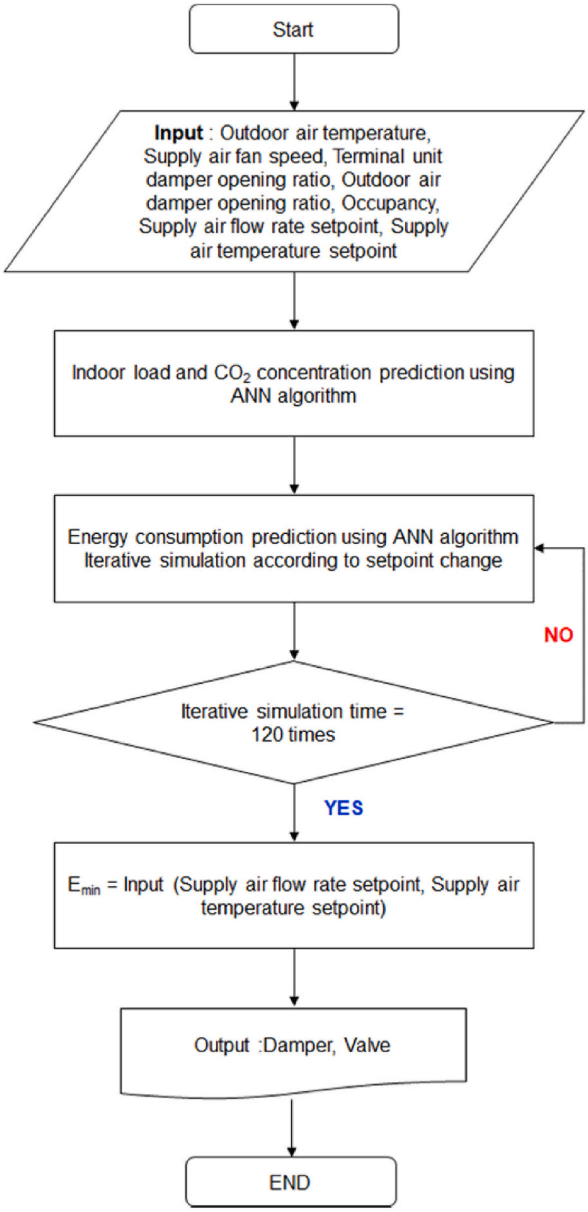


Fig. 3. ANN based control algorithm of VAV terminal unit.

through the variable frequency drive (VFD), and dual maximum control logic is applied to the existing terminal unit control method. To control the VAV terminal unit, an indoor load, CO_2 concentration, and energy consumption prediction model was developed using the outside air temperature, supply fan speed, outside damper opening ratio, number of occupants and terminal unit damper opening ratio as input data. The VAV terminal unit is controlled using the supply air flow rate and supply air temperature setpoints indicating the minimum energy consumption using prediction model. Fig. 4 shows Schematic diagram of target building and VAV terminal unit system.

3.2. Energy simulation

In this study, the TRNSYS17 simulation program was used to analyze the optimal energy consumption of the VAV system. TRNSYS is a detailed building analysis program, where the user performs simulation by connecting components to each other. And the system information of the laboratory was modeled using Simulation Studio. The simulation results collected VAV system operation data,

Table 1
Overview of VAV system in target building.

Category				Contents
Building	Location			Gyeongsan-si, Gyeong-buk, South Korea
	Use			Laboratory in University
	Area			116.64m^2
System	AHU	Type		Single duct VAV system with return fan
		Supply fan	Rated air flow rate	12000CMH
			Rated static pressure	961Pa
			Rated power	5.5 kW
		Return fan	Rated air flow rate	9600CMH
			Rated static pressure	343Pa
			Rated power	3.7 kW
	Terminal Unit	Type		Terminal unit with reheat coil
		Rated air flow rate		1360CMH
		Capacity if reheating coil		4649 kWh
System Operation	Operation time			24 h
	Indoor temperature setpoint			24 °C

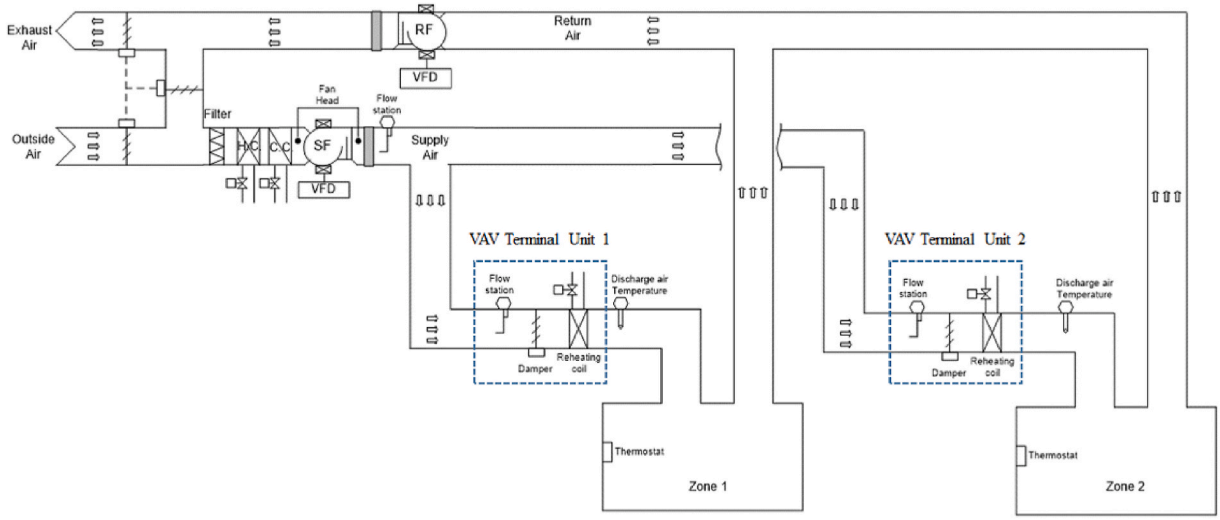


Fig. 4. Schematic diagram of target building and VAV terminal unit system.

Table 2
Boundary condition for Trnsys 17 simulation.

Category		Contents
Thermal Transmittance [32]	Outdoor Wall	0.310 W/m^{2}K
	Indoor Wall	0.508 W/m^{2}K
	Floor	0.039 W/m^{2}K
	Roof	0.316 W/m^{2}K
Internal heat gain [32]	Occupancy	Seated, Light work, typing 150 W/person
	Light	13 W/m^2
	Equipment	16 W/m^2
Schedule	Occupancy	00:00–09:00 : 0% 09:00–18:00 : 100% 18:00–24:00 : 0%
	Light	00:00–09:00 : 0% 09:00–18:00 : 100% 18:00–24:00 : 0%
	Equipment	00:00–09:00 : 10% 09:00–18:00 : 100% 18:00–24:00 : 10%

indoor thermal environment data, indoor CO_2 concentration and indoor load.

Data in TMY format were used for the outdoor conditions for the simulation. Table 2 shows the Boundary condition for Trnsys 17 simulation [32]. The building material properties, internal heat gains and schedule were entered for energy simulation. Since the target building was used as a laboratory, the amount of heat generated by the occupants who sit and do light work, such as working with documents, was considered the internal heat generated by the occupants. Likewise, the lighting and devices generated internal heat was calculated as the amount of heat per floor area of the target building.

The boundary condition of simulation was performed in TRNBuild by changing the density of occupants and devices (computers and monitors) that affect the indoor load. The air flow rate setpoint was reflected in the supply air flow rate calculation formula to control the air flow rate supplied to the target building. In addition, the supply temperature setpoint controlled the temperature of reheat coil through the controller (Type 1669). Fig. 5 shows the simulation diagram for learning data of ANN based prediction model.

In this study, as there is a limit to the data collected from the target building, iterative simulations were performed by changing the variables that could affect the indoor condition and energy consumption. The collected data was used as learning data used to develop a prediction model. Learning data was collected at 1 h intervals through simulation, and the data were collected by changing indoor heat (persons occupant, equipment) conditions and VAV terminal unit setpoints (minimum air flow rate, supply air temperature). A total of 720 cases were constructed according to each variable combination and repeated simulations were performed. Fig. 6 shows simulation case for learning data collection of prediction model. And Table 3 shows the range of learning data collected through simulation. The setpoint of air flow rate was set in the range of 100CMH to 1500CMH at intervals of 100CMH. The setpoint of supply temperature was set in the range of 26 °C–33 °C at intervals of 1 °C. The number of occupancy and equipment density values mean the number of occupants of 0–5 people, and in the simulation, it is calculated by multiplying the indoor heat gain (occupancy and equipment) in Table 2 for each number of occupants. There is a problem in that the number of data becomes too large to construct the learning data by building the entire data throughout the year by simulation for building the input data. The period of 1500 h (about 2 months) in winter, in which the minimum air flow rate setpoint of the VAV terminal unit affects, was selected as the simulation period. Accordingly, a total of 1,080,000 data sets were constructed as training data.

Fig. 7 shows simulation diagram for ANN based optimal control of VAV terminal unit. Through Trnsys, building and VAV terminal unit operation data is transmitted to the R and predicted in real time. The indoor load, CO_2 concentration and energy consumption are predicted through the R. The supply temperature and air flow rate setpoints that minimize energy consumption derived from R are sent to Trnsys.

3.3. ANN based prediction model

ANN based prediction model was developed using R. First, the composition, use function, and learning method of the input, hidden and output layer are determined. And the next step is to optimize the model to derive the optimal number of hidden layers and neurons to improve the accuracy of the prediction model. And the performance analysis and applicability of the prediction model are analyzed

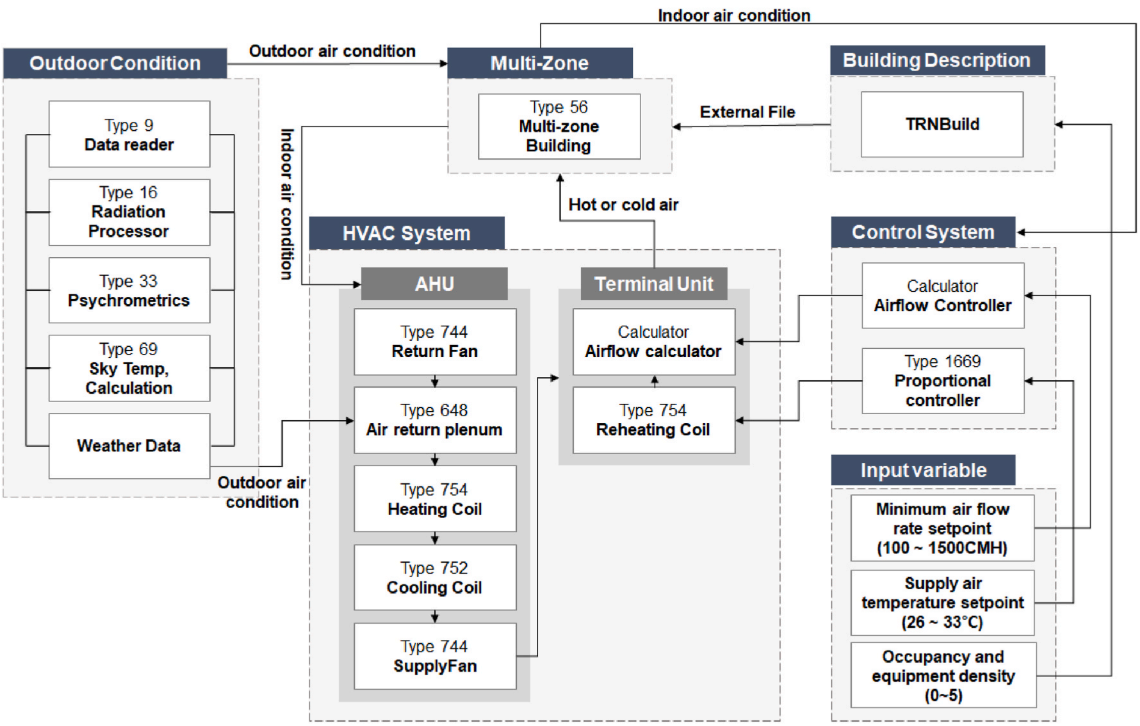


Fig. 5. Simulation diagram for learning data collection of ANN based prediction model.

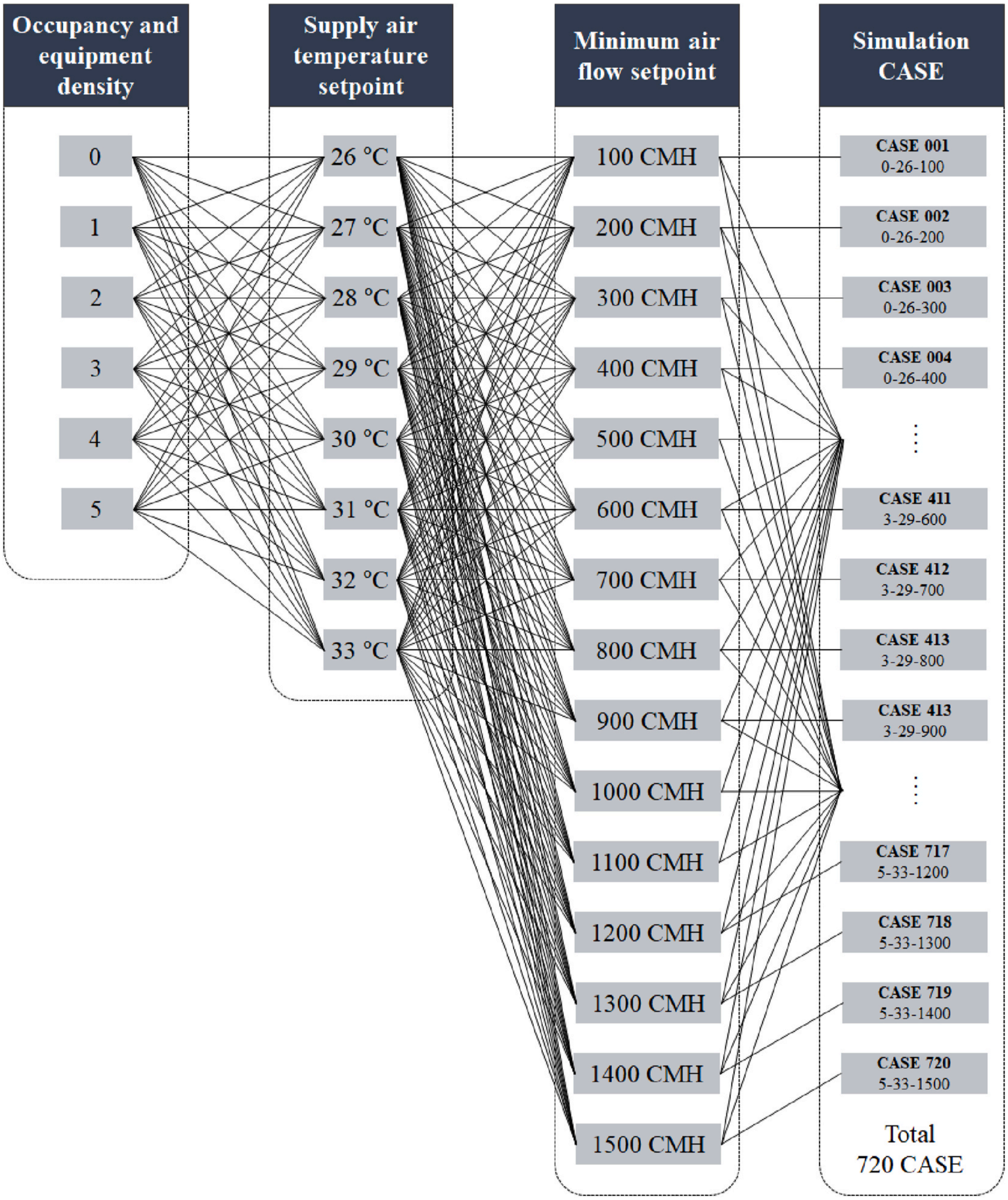


Fig. 6. Simulation case for learning data collection of prediction model.

Table 3
Input data of simulation for learning data collection.

Variable	Input data
Occupancy and equipment density	0, 1, 2, 3, 4, 5
Minimum air flow set-point (CMH)	100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200, 1300, 1400, 1500
Supply air temperature set-point (°C)	26, 27, 28, 29, 30, 31, 32, 33

through comparative analysis of the prediction result of the developed energy prediction model and the simulation result value. The collected data was 8760 sets for the indoor load and CO_2 prediction models, and the energy consumption prediction model was 1080000 sets, and 85% was used as training data and 15% as validation data of the total data sets. A trial and error method was used to determine the number of hidden layer and neurons [32]. The Adaptive Moment Estimation (Adam) algorithm was used to optimize the

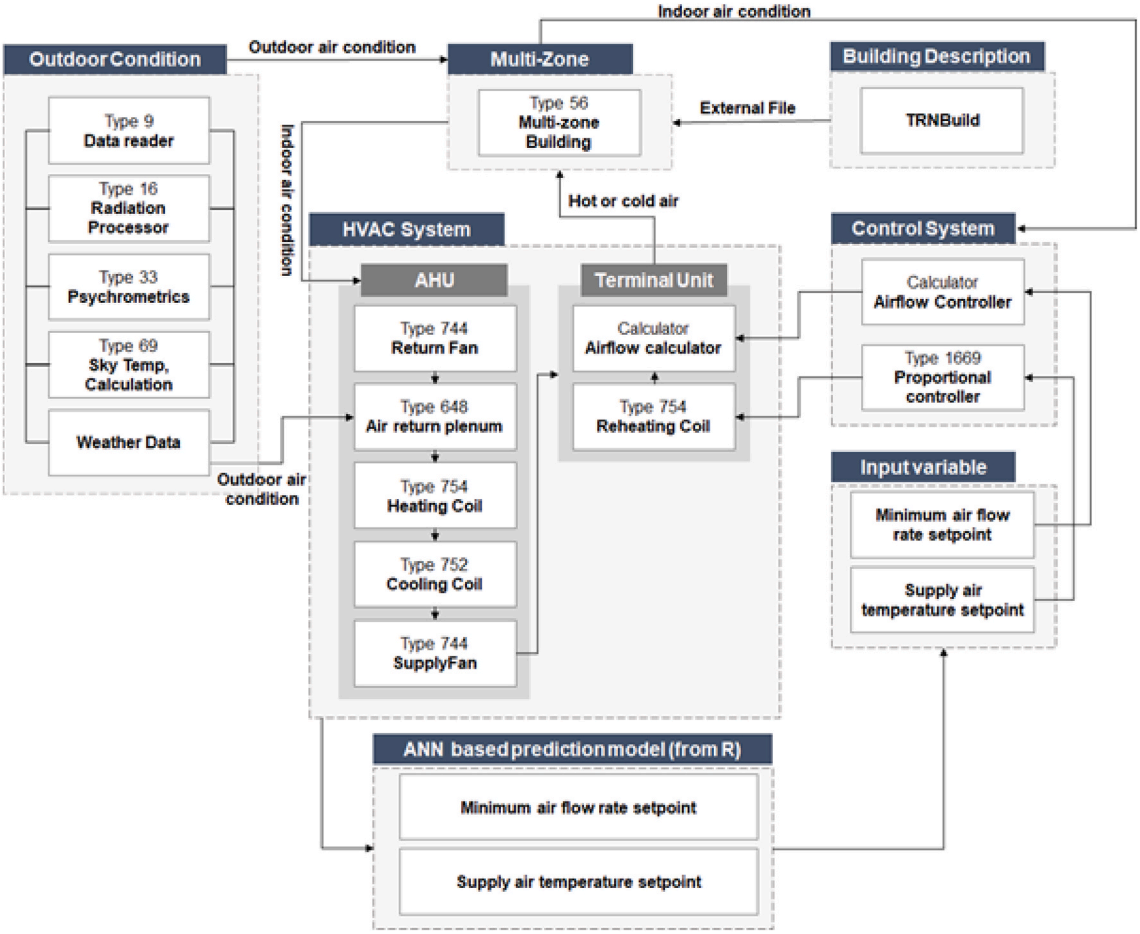


Fig. 7. Simulation diagram for ANN based optimal control of VAV terminal unit.

Table 4
Input parameter of indoor load, CO_2 concentration and energy consumption prediction model.

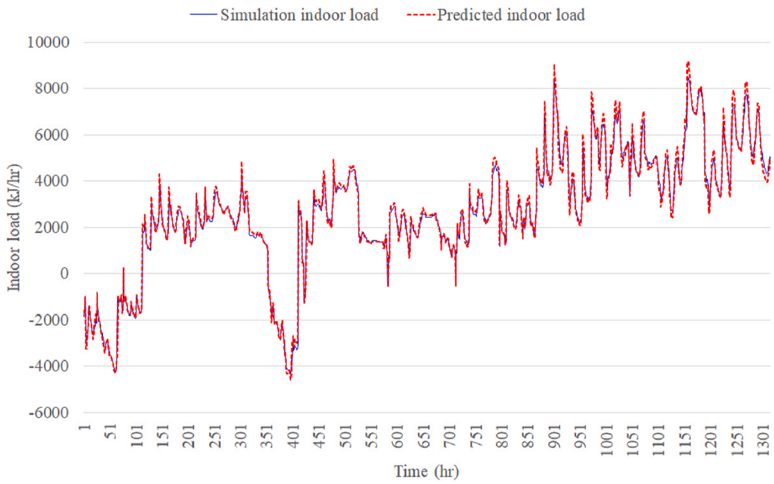
Category	Total Data set (Trains/ Validation)	Activation function	Loss function	Optimization algorithm	Epoch	Number of layer and neuron (layer/neuron)		
						Input	Hidden	Output
Indoor load	8760 set (7,446set/1,314set)	Sigmoid	Mean squared error	Adam	5000	1/4	2/9	1/1
CO_2 concentration						1/4	2/11	1/1
Energy consumption	1,080,000 set (918,000set/ 162,000set)					1/4	3/7	1/1

prediction model, and the activation function used a sigmoid function, the loss function used the mean squared error [35]. Table 4 shows input parameter of indoor load, CO2 concentration and energy consumption prediction model by ANN in R.

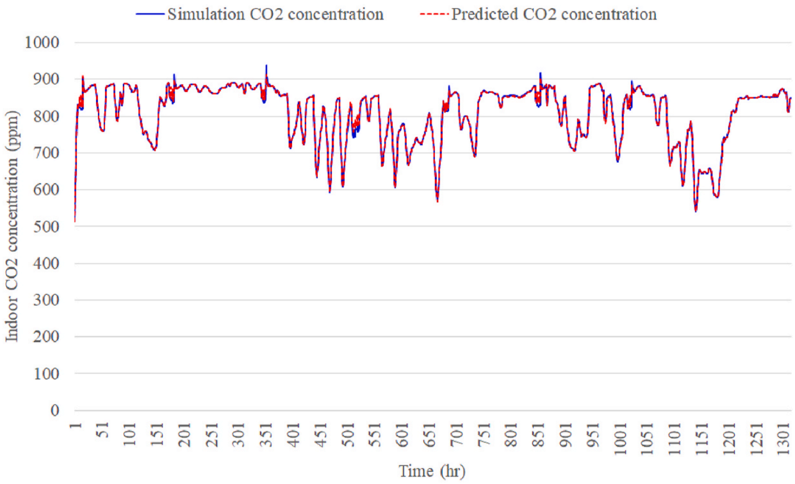
To evaluate the indoor load, CO_2 concentration and energy consumption prediction model, the accuracy was evaluated using mean bias error (MBE) and coefficient of variation of root mean square error (CvRMSE). MBE means the total error of the predicted data and CvRMSE is a method of analyzing the error through the degree of variance. As shown in Equations (2) and (4), the accuracy of the prediction model was evaluated using MBE and CvRMSE [36].

Prediction model is calculated using various input variables [37]. The uncertainty of the prediction model is caused by the accuracy and bias error of the input variables. The uncertainty of the prediction model according to the input variables can be estimated using the Taylor series method as in Equation (11) [38,39].

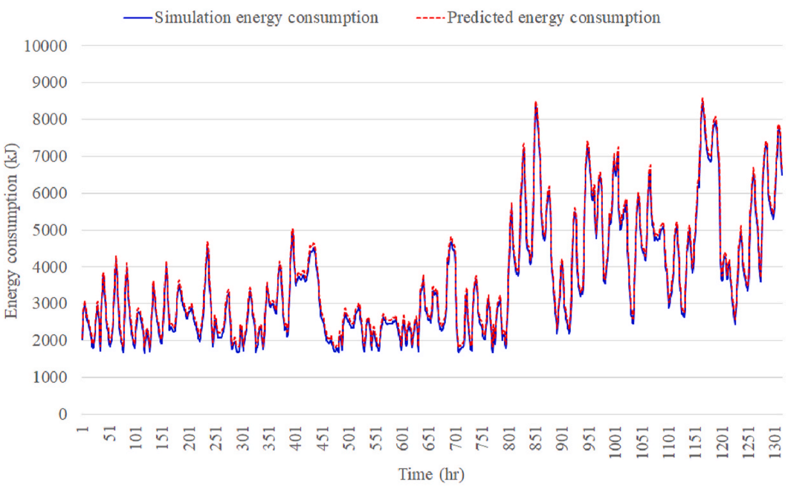
$$MBE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} \times 100 \tag{9}$$



(a) Indoor load



(b) CO_2 concentration



(c) Energy consumption

(caption on next page)

Fig. 8. Comparison of prediction model and actual data.

$$C_vRMSE = \left(\sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \Big/ n} \Big/ \overline{y} \right) \times 100 \tag{10}$$

$$u = \sqrt{\sum_{t=1}^{s} \left(\frac{\partial y}{\partial v_t} \delta v_t \right)^2} \tag{11}$$

where

$y$actual value
$\hat{y}$prediction value
$\overline{y}$average value
nnumber of value
$u$uncertainty error
$v$variable of prediction model
tnumber of variable

3.4. Simulation CASE

To evaluate the performance of the developed ANN based optimal control method, it was compared with the existing VAV terminal unit control method. For the existing control method, the dual maximum control logic suggested by ASHRAE was selected. The dual maximum control logic, a general VAV terminal unit control algorithm, has the advantage of being able to set the maximum supply air flow rate of the VAV terminal for the heating and cooling. The dual maximum control logic can also set the minimum supply-air flow rate of the VAV terminal unit lower than that set by the single maximum control logic VAV terminal unit control algorithm. In addition, it is possible to remove the heating load of a building by changing the supply air temperature under the condition of the minimum supply-air flow rate of the VAV terminal unit through the use of the supply air temperature sensor. Hence, the dual maximum control logic was used in a VAV terminal unit control algorithm using a fixed setpoints for the VAV terminal unit in the target building of the chosen building.

4. Result and discussion

4.1. ANN based prediction model

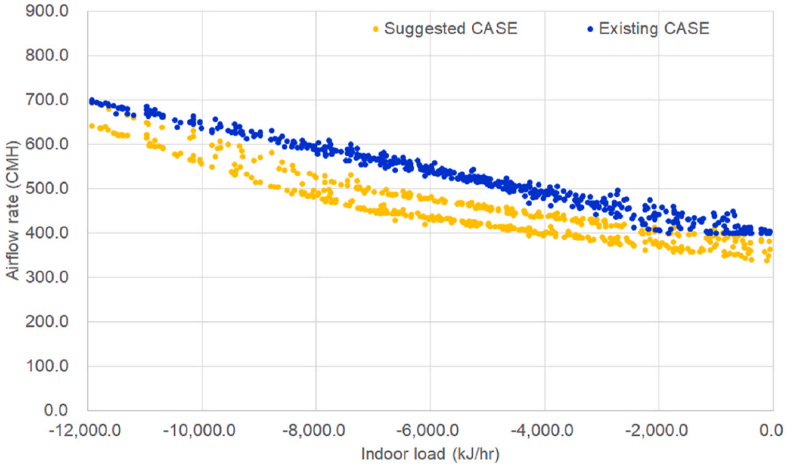
The accuracy of ANN based prediction model was validated and evaluated using CvRMSE and MBE [33]. Fig. 8-(a) shows comparison of indoor load prediction model and simulated data. The developed indoor load prediction model was analyzed for comparison between the predicted indoor load and the simulated indoor load using data for verification. As a result of the analysis, MBE was −1.8%, CvRMSE was 3.4%, and R^2 was 0.97, indicating high accuracy. Fig. 8-(b) shows comparison of CO_2 concentration prediction model and simulated data. As a result of the analysis of the CO_2 concentration prediction model, the MBE was −3.2% and the CvRMSE was 5.4%, R^2 was 0.99 confirming the excellent performance of the prediction model. Fig. 8-(c) shows comparison of energy consumption prediction model and simulated data. As a result of the analysis of the energy consumption prediction model, MBE was 6.4% and CvRMSE was 8.5%, R^2 was 0.98 which can be confirmed as a meaningful model as a value that is less than the standard for verification of measurement data for each hour in ASHRAE Guideline 14 (MBE less than 10%, CVBMSE less than 30%). Table 5 shows performance validation result of prediction model. The uncertainty of the predictive model occurs depending on the error range of the input data. The uncertainty of the indoor load, CO_2 concentration and energy consumption were within ±7.9%, ±5.6% and ±9.3%.

4.2. Analysis of ANN based optimal control

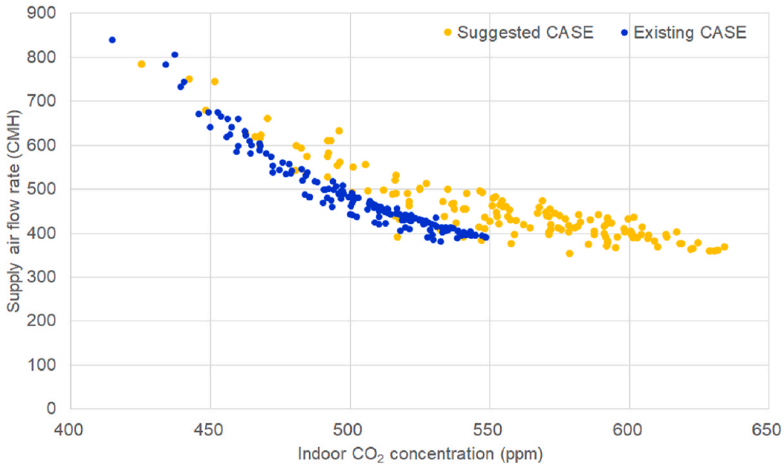
The control performance of the existing control algorithm to which dual maximum control logic is applied (existing CASE) and the ANN based optimal control algorithm (suggested CASE) developed in this study were compared. As shown in Fig. 9-(a), when suggested CASE was applied, it was confirmed that the supply air flow rate decreased under all load condition during the heating season

Table 5
Performance validation result of prediction model.

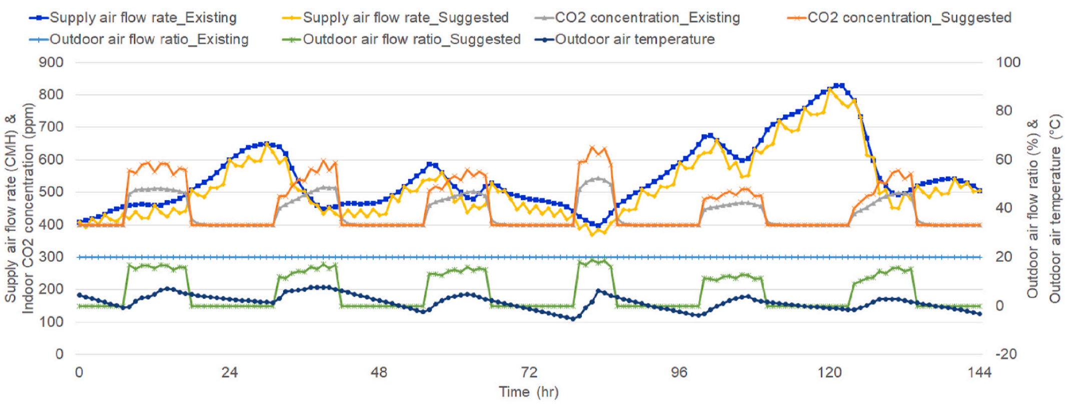
Prediction model	Indoor load	Indoor CO_2 concentration	Energy consumption
MBE (%)	−3.2	−1.8	6.4
CvRMSE (%)	5.4	3.4	8.5
R^2	0.97	0.99	0.98
Uncertainty (%)	±7.9%	±5.6%	±9.3%



(a) Correlation between the Supply air flow rate and Indoor load



(b) Correlation between the Supply air flow rate and Indoor CO_2 concentration



(c) Series data of VAV terminal unit

Fig. 9. Comparison of supply air flow rate between the existing and suggested CASE.

compared to existing CASE, and it was confirmed that the maximum air flow rate decreased by about 150CMH. Fig. 9-(b) shows comparison of supply air flow rate according to indoor CO_2 concentration. In the suggested CASE, it can be seen that the supply air flow rate decreased and the indoor CO_2 concentration increased. As the supply air flow rate decreased, the indoor CO_2 concentration increased, but the indoor CO_2 concentration satisfies the standard within 1000 ppm. Fig. 9-(c) compares the results of the existing and the suggested CASE in winter season. The air flow rate and the indoor CO_2 concentration and outdoor introduction rate were compared. In the suggested CASE, the supply air flow rate decreased at all times compared to the existing CASE. The outdoor airflow rate of suggested CASE decreased compared to fixed value (20% of maximum air flow rate) of existing CASE.

As for the supply temperature, existing CASE provided the maximum supply temperature (32.2 °C) under most load conditions, and suggested CASE provided various supplies from 26 °C to 31 °C from −7200 to 0 kJ/h. It shows the temperature, and it was confirmed that the maximum supply temperature was supplied at the load below that, as shown in Fig. 10.

Fig. 11-(a) shows comparison of energy consumption. In the case of the supply fan, 308,535 kJ was consumed in existing CASE, and 257,121 kJ was consumed when suggested CASE was applied. By resetting the setpoint, the fixed minimum air flow rate was reset according to each load and indoor air quality conditions, and it was confirmed that the supplied air flow rate was reduced and, accordingly, about 16.7% of fan energy was reduced. In the case of reheat coil energy, 5,197,208 kJ was consumed in existing CASE and 4,182,638 kJ was consumed when suggested CASE was applied. It was confirmed that the reheat coil energy was reduced by about 19.5% due to a decrease in the set air flow rate and a change in the supply temperature setpoint, such as reducing the energy of the supply fan. Fig. 11-(b) shows comparison of energy consumption of reheating coil according to indoor load. Reheating coil energy decreased in most of the heating load section, and it was confirmed that the most reheat energy decreased when −4000 kJ/h. As can be seen in Fig. 10, it is seems that the reheat energy is reduced because the supply temperature that has passed through the reheat coil is reduced by about 7 °C.

5. Conclusion

This study improved the control algorithm of the existing VAV terminal unit by predicting the indoor energy consumption by using the indoor load and CO2 concentration prediction models of the building. Further, this study reset the setpoints of the VAV terminal unit corresponding to the minimum energy consumption. The key aspects of this study are as follows.

An ANN-based indoor load, CO2 concentration and energy consumption prediction model was developed using the operation data of the VAV system. For the load prediction model, supply fan speed, VAV damper position, outdoor temperature and number of occupants were selected as input variable. As an accuracy of indoor load prediction model, MBE was −1.8%, CvRMSE was 3.4%, and R2 was 0.97. For the CO2 prediction model, the outdoor air damper opening ratio, the supply fan speed, the VAV damper position and the number of occupants were selected as input variable. As an accuracy of CO2 concentration prediction model, the MBE was −3.2% and the CvRMSE was 5.4%, R2 was 0.99. For the energy prediction model, the CO2 predicted value, the load predicted value, the setpoints of supply air flow rate and the supply temperature were selected as input variable. As an accuracy of the energy consumption prediction model, MBE was 6.4% and CvRMSE was 8.5%, R2 was 0.98.

In addition, a method for optimizing the supply air flow rate and temperature setpoint using the developed predictive model was proposed. The energy consumption of VAV terminal unit system according to various setpoint combinations was predicted, and the setpoint of the minimum energy consumption was used for control. Compared to the existing control method, the supply air flow rate

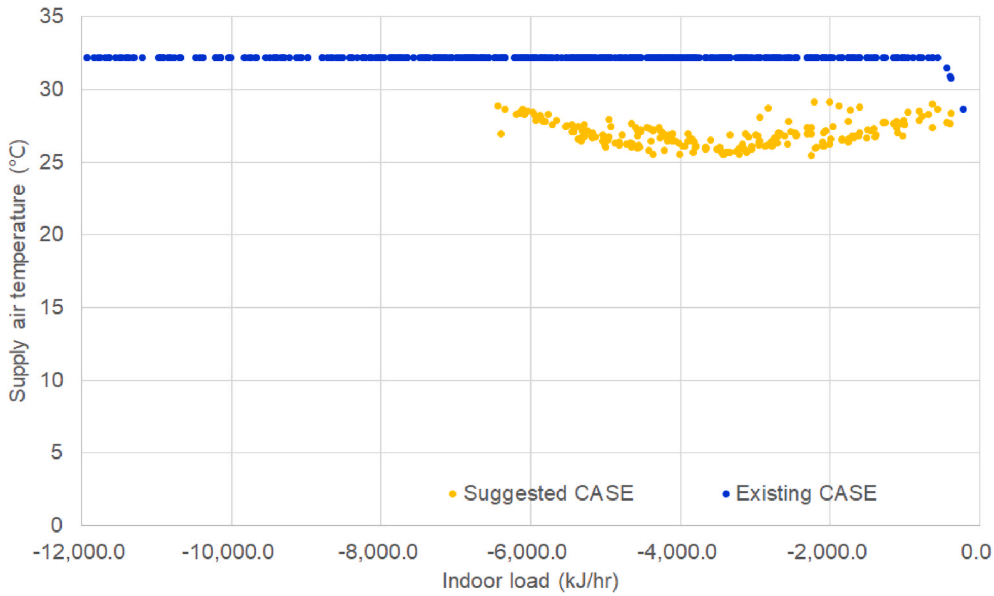
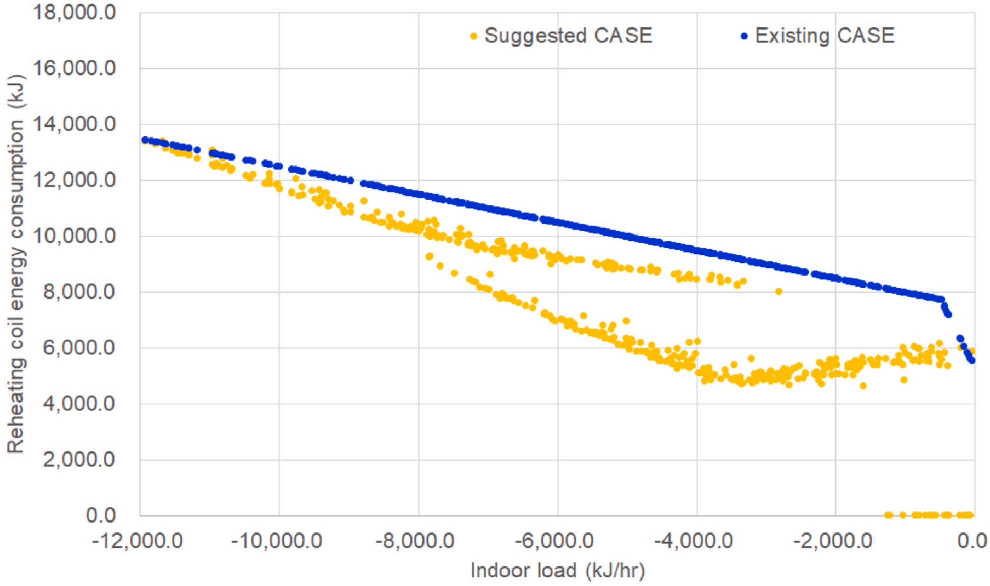
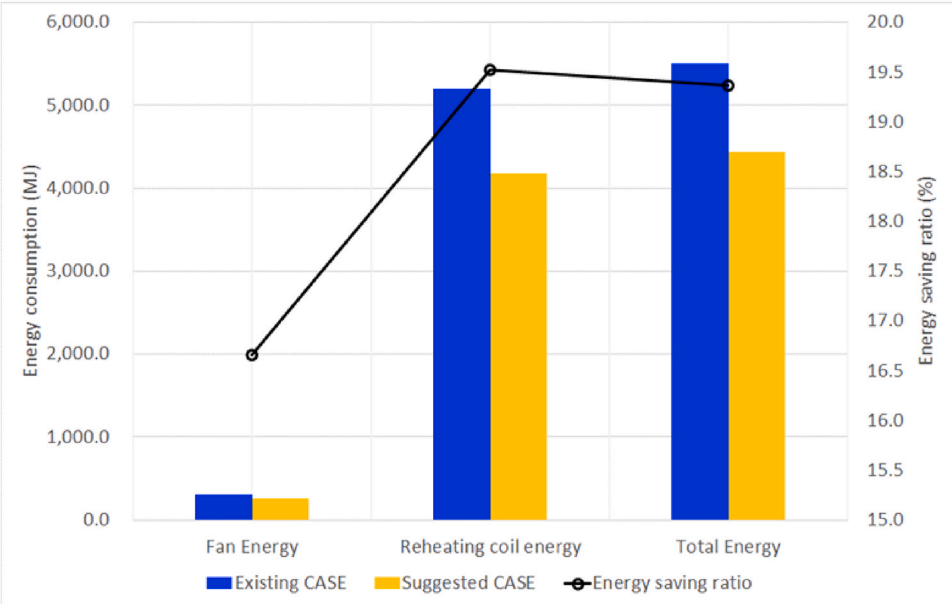


Fig. 10. Comparison of supply air temperature between the existing and suggested CASE.



(a) Correlation between the reheating energy consumption and Indoor load



(b) Annual energy consumption

Fig. 11. Comparison of energy consumption between the existing and suggested CASE.

was reduced by up to 25% in the ANN based control method. In addition, it was confirmed that the existing fixed supply temperature (32.2 °C) can be supplied up to 7 °C lower. The comparison showed that the heating energy consumption of the target building under the ANN based control method in the VAV terminal unit reduced 16.7% of supply fan energy consumption and 19.5% of reheat coil energy consumption compared to the existing CASE using the fixed setpoints.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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